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Elastic neural network method for multi-target tracking task allocation in wireless sensor network☆

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ABSTRACT

Aiming at the task allocation of collaborative technique in wireless sensor network, a method for optimized task allocation based on elastic neural network is proposed under the background of multi-sensor tracking. First a model of multi-coalition tracking multi-target is designed. Then disjoint fully connected subgraphs of neurons are constructed to solve the problem of optimized task allocation in tracking multi-target and the increment of system energy consumption when dynamic coalitions compete and conflict for the resource of sensor nodes. Compared with the conventional method, simulation results show that the energy consumption of the tracking system is reduced significantly and the tracking accuracy is improved greatly, demonstrating the effectiveness of elastic neural network in handling the optimized task allocation problem of multi-sensor tracking multi-target.

1. Introduction

Wireless Sensor Network (WSN) is a kind of intelligent network system with autonomous measurement and control ability, which can finish the designated task according to the environment independently. WSN is composed of thousands of wireless sensors generally densely distributed over the surveillance area without human participation. The sensor nodes are typically small in size, cheap and of low cost with limited communication and computation abilities. The aim of WSN is to detect, gather and process the information in its surveillance area collaboratively and provide the information to users [1]. By a reasonable combination of multi-sensors, WSN can be complementary in performance and function, which improves the stability and reliability of the system and the confidence of data. Besides, it can cover a larger area and observe the target from different positions. Hence, for such features, WSN can be applied to many aspects very well, such as military reconnaissance, and battle field surveillance, especially target tracking [2].

Since each node is restrained in resources such as energy, processing time and communication bandwidth [3], sensor nodes cannot achieve complex tasks independently. Then, they should collaborate with each other and achieve complex information gathering and processing tasks. Task allocation is how to select sensor nodes to track targets [4]. Since WSN is of exceedingly large scale, has a dynamic topological structure and strictly restrained resource, new challenges of collaborative task allocation mechanism arise. So how to realize effective task allocation mechanism and prolong the lifetime of WSN should be the main factors considered [5].

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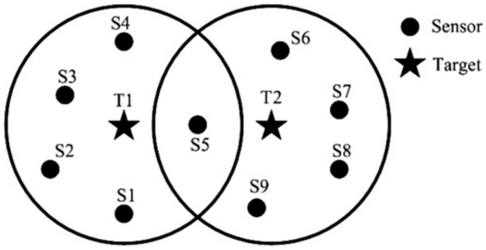

Fig. 1. Two coalitions tracking two targets.

Generally, the dynamic task allocation of WSN in tracking targets is realized through collaboration of sensors based on dynamic coalition. When in the process of surveillance over some specific region, a sensor may detect a target within its sensing range. To achieve the task of tracking, it must cooperate with relevant sensors in the network. Then it selects a set of sensor resources that can help complete the tracking task to form a dynamic coalition.

In order to calculate exact location of targets, three sensors are needed to form a dynamic coalition for one particular target tracking task. Meanwhile, because of the restrained ability of a sensor, one sensor should be allocated to join in only one dynamic coalition to track one target. Hereby, several dynamic coalitions are needed when there are several targets moving which may cause coverage areas of different coalitions to overlap. Now that different tracking tasks may need the same sensor, there will be competitions and conflicts appearing for sensor resource between coalitions. As shown in Fig. 1, when there are two targets appearing in the area, sensor S5 needs to decide to track target T1 or T2. In this case, the crucial sensor resource must be allocated to optimal task to avoid increasing the system energy consumption dramatically.

A variety of researches have focused on task allocation in multi-sensor collaborative tracking multi-target. In Reference [6], the authors only consider the case that the sensors are distributed in an equilateral triangle fashion. They propose to choose three sensors nearest to the target to form a group, without considering factors such as random distribution of sensors, energy consumption for communications and localization accuracy. Likewise, although the autonomous node selection method raised in Reference [7] takes into consideration of factors such as energy consumption and localization accuracy, it does not mention multi-target tracking task allocation and the following possible competition and conflict for sensor resource. At the same time, Nash [8] proposes to use linear programming in allocation of sensors for tracking targets, and Castaon [9] presents a method taking advantage of dynamic programming for multi-target. Unfortunately, the optimal task allocation for multi-sensor multi-target tracking not only has complex restrictions but also is NP-hard in combination. Although the optimal allocation result can be got theoretically by traditional mathematical programming, it often fails to fulfill practical need confined by dimensions.

Aiming at the task allocation of collaborative techniques in WSN, considering factors such as random distribution of sensors, energy consumption for communications and localization accuracy, multiple elastic neural network modules are proposed to achieve task allocation of system.

2. Main results

2.1. Problem description

For the purpose of multi-target tracking, several dynamic coalitions for tracking targets separately are needed. One dynamic coalition comprised of three sensors is used to track one target. Considering such factors as the random distribution of sensors, communication energy and localization accuracy of wireless sensor nodes, the minimum cost criterion is adopted here for optimized allocation of sensors for targets. The cost contains communication energy and localization error.

It is obvious that the selection of sensor nodes in dynamic coalitions is to get as small circle error probability (CEP) as possible and reduce the energy consumption as well. When bearings-only target tracking and localization in 2-D is considered, the CEP showing the localization accuracy can be defined as [10]:

$$CEP = 0.75\sqrt{\mathrm{trace}(J^{-1})} \tag{2.1}$$

where J is Fisher information matrix:

$$J = \sum_{n\in W_c} \frac{1}{\sigma_n^2 r_n^2} \begin{bmatrix} \cos^2\beta_n & -\sin\beta_n\cos\beta_n \\ -\sin\beta_n\cos\beta_n & \sin^2\beta_n \end{bmatrix}. \tag{2.2}$$

Here, W_c is the set of sensors forming coalitions, σ_n is the orientation measurement deviation of sensor n, β_n is the azimuth angle of target measured by sensor n and r_n represents the relative distance between the target and sensor n.

Each sensor node draws energy from the battery to sense, data process and communicate. Typically, communication requirements dominate the energy budget. This paper exploits the communication energy model introduced in Reference [7] and the energy used for communication is:

$$E = \sum_{n \in W_c} \sum_{k \neq n, k \in W_c} [l_n e_{\mathrm{amp}} d_{nk}^4 + l_n e_{\mathrm{ele}}]. \tag{2.3}$$

The energy per bit to run the electronics and power amplifiers are $e_{\mathrm{ele}} = 50$ nJ/bit and $e_{\mathrm{amp}} = 0.0013$ pJ/bit/m^4 respectively. l_n is the data transferred at sensor node n and d_{nk} is the distance between sensor node n and the selected node k. Hence, the whole energy E is decided by d_{nk}, and the problem of getting the lowest energy consumption changes to make the sum of d_{nk} smallest.

Now suppose that there are N sensor nodes and M targets ($N > 3M$) in this paper. The aim of optimized allocation is to get the lowest cost including energy consumption and localization error of the sensor system.

Assume $W_s = \{s_1, s_2, \ldots, s_n, \ldots, s_N\}$ is the set of N sensor nodes, $W_t = \{t_1, t_2, \ldots, t_m, \ldots, t_M\}$ is the set of M targets and $W_c = \{c_1, c_2, \ldots, c_m, \ldots, c_M\}$ is the set of M coalitions, where each element $c_m = \{s_{m1}, s_{m2}, s_{m3}\}$ ($s_{m1}, s_{m2}, s_{m3} \in W_s$) represents a dynamic coalition composed of three sensors, corresponding to tracking target t_m.

The matrix describing this task allocation can be defined as:

$$A = \begin{bmatrix} a_{11} & a_{12} & \ldots & a_{1N} \\ a_{21} & a_{22} & \ldots & a_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ a_{M1} & a_{M2} & \ldots & a_{MN} \end{bmatrix}$$

where a_{mn} is 0–1 value. If $a_{mn} = 1$, the nth ($n = 1, 2, \ldots, N$) sensor will be designated to track target m ($m = 1, 2, \ldots, M$), otherwise $a_{mn} = 0$. Then the answer to the problem of allocating sensor resource resides in figuring out each element $c_m = \{s_{m1}, s_{m2}, s_{m3}\}$ ($s_{m1}, s_{m2}, s_{m3} \in W_s$) of W_c under minimum cost criterion.

Therefore, the model for the problem of optimized tracking task allocation of multi-sensor to multi-target can be written as:

Minimize:

$$\sum_{m=1}^{M} \sum_{n=1}^{N} a_{mn} d_{mn} + CEP.$$

Subject to:

(1) Sensor s_n can join in only one coalition c_m. Otherwise the sensor sleeps.

$$\sum_{m=1}^{M} a_{mn} \leq 1, \quad n = 1, 2, \ldots, N.$$

(2) Locating target t_m needs a coalition c_m comprised of three sensors.

$$\sum_{n=1}^{N} a_{mn} = 3, \quad m = 1, 2, \ldots, M.$$

(3) The sum of all elements in the task allocation matrix should be

$$\sum_{m=1}^{M} \sum_{n=1}^{N} a_{mn} = 3M, \quad m = 1, 2, \ldots, M, n = 1, 2, \ldots, N.$$

Using the objective function, the total cost of the task and resource allocation by matching all possible tracking tasks with sensors can be obtained, and the result corresponding to the lowest cost is chosen as the result of optimized task allocation. The first constraint can solve the competition and conflict problem of one sensor for multi-coalition when tracking multi-target.

Generally speaking, the optimization problem above can be viewed as 0–1 integer programming in essence, which is NP-hard. Here, an elastic neural network method is proposed to solve this problem in order to get an optimized result for task allocation.

2.2. Multiple elastic modules

Multiple elastic neural network modules (MEM) are presented as a significant extension to self-organizing map (SOM) [11]. The MEM which generalizes the self-organizing principles of the SOM is introduced to make the model amenable to a wide range of difficult optimization problems, such as computer vision and DNA sequence. This paper will take N nodes tracking M targets for example to show the application of MEM.

MEM is a kind of network with input and output layers. The neurons of input layer are initialized to position vectors of sensors which form the coalitions. The neurons of output layer can be separated into M subgraphs which are composed

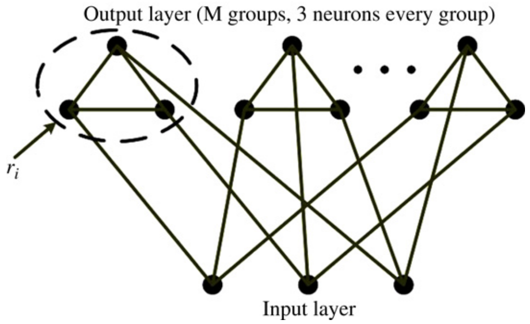

Fig. 2. The configuration of MEM.

of three fully connected neurons. At the same time, the subgraph is not connected together. Each subgraph B_q ($q = 1, 2, \ldots, M$) represents the information of the allocation result of a dynamic coalition. The associated weights connecting neurons of output layer are distance between them.

The configuration of MEM is illustrated in Fig. 2. A unique feature of the MEM model is the use of a dynamic receptive field r_i(RF) [12] with each neuron i. The size of a neuron's RF is determined according to:

$$r_i = p_i h_i + e_i + \varepsilon_i \tag{2.4}$$

h_i and e_i represent locking value and expectation value of the neuron i respectively. The noise parameter ε_i related to the sensor's detection error is a small constant which determines the minimum RF size of all neurons. The p_i term is a measure of the local deformation of the graph about neuron i. For the multi-sensor multi-target tracking task allocation application, our desired objective is to get the least cost of dynamic coalition formed. Therefore, p_i can be defined as:

$$p_i = \sum_{j \in L_i} \|X_i - X_j\| + CEP \tag{2.5}$$

where $L_i = \{j | g_{ij} = 1\}$. $g_{ij} = 1$ if neuron i is a direct neighbor of neuron j. X_i is the position vector of neuron i. In this formulation p_i is the sum of cost of neuron i and its neighbor neurons. Take three sensors forming a dynamic coalition for example, we can make a simplification to this function by setting p_i equal to the sum including CEP and the perimeter of the triangle formed by the three neuron vertices.

2.3. Task allocation algorithm based on MEM

Using MEM to solve the allocation problem, the disjoint fully connected subgraphs of neurons can be constructed. Then the problem changes into finding a dynamic coalition composed of three nodes in the surveillance area and getting the optimal result. With the attraction of the objective function in optimal problem, the receptive field of the elastic neural network converges and locks each member of the coalition.

Formally, the task allocation algorithm based on MEM involves the following steps:

(1) Initialize each neuron of subgraph. Randomly assign neurons with different position vectors in the surveillance area.

(2) Randomly select a position vector X_s of sensor node s as the input of one neuron of the input layer. Since there are three neurons in the input layer, X_s should be the input of different neuron of input layers each time to make sure that each neuron has the chance to compete.

(3) Construct a set B according to coalition covering sensor node s correspond to the neuron i.

$$B = \{i | X_i \in B_q \cap \|X_s - X_i\| \le r_i\} \tag{2.6}$$

where X_i is the position vector of neuron i and the coalitions corresponded to B_q can cover sensor node s.

(4) If set B is empty, repeat this procedure by picking another random sensor node. When a nonempty set B is generated, the neurons within this set are allowed to compete, using a WTA mechanism, to find the closest neuron X_i^* to the input:

$$X_i^* = \min_{i \in B_q} \|X_s - X_i\|. \tag{2.7}$$

(5) Adjust the locations of winning neuron and its neighbors according to:

$$\begin{aligned} X_i^* &= X_i^* + \alpha(X_s - X_i) \\ X_j &= X_j + \beta_j (X_s - X_j), \quad j \ne i, j \in B_q \end{aligned} \tag{2.8}$$

where α and β_j denote the learning rate. The value of α is less than 1. β_j is defined as $\beta_j = \frac{\alpha p_i}{p_i + \eta}$. The elasticity parameter η is used to control the degree of elasticity of these modules.

(6) Gradually adjust the receptive field r_i and r_j.

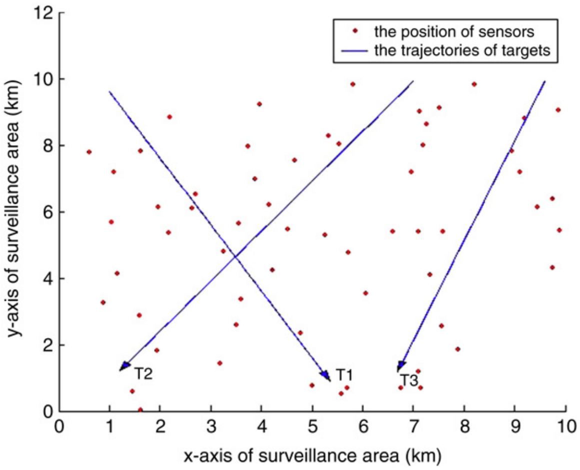

Fig. 3. Target trajectories and sensor distribution.

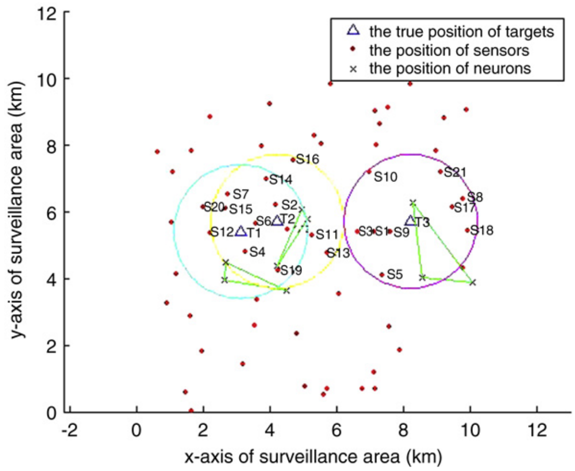

Fig. 4. The initial random network state and the position of targets in MEM.

(7) When $p_i \leq 3\varepsilon_i$, we can determine that the subgraph has locked coalition members. The sensor nodes locked by every neuron in subgraph are the ultimate coalition members using task allocation algorithm.

(8) Otherwise, go back to step (2).

3. Simulation results

The unit of the coordinate is kilometer in the simulation. There are three targets ($T1$, $T2$, $T3$) in a rectangle area. Three targets are in uniform linear motion. Sixty passive sensors ($S1, S2, \ldots, S60$) are distributed randomly. Each sensor with detection range of 2 km can only obtain the azimuth angle of the target tracked and the root mean square (RMS) error of the angle is 0.01 rad.

The sampling interval is 1 s. The iterative of MEM is 90. The learning rate α of the winning neuron is 0.05. The elasticity parameter η of the neighbor neurons of the winning neuron is 3. The data transferred at sensor node is 100 bits. Fig. 3 shows the trajectories of three targets and the distribution of sixty sensors.

During each sampling interval, MEM algorithm is used to get the optimized allocation results (Fig. 4). Take $t = 16$ s for example, Fig. 5 is the specific result of task allocation result by MEM. Table 1 gives the allocation result, localization result and energy consumption. Fig. 6 is the tracking error for $T3$ using Kalman Filter Algorithm.

To illustrate the effectiveness of the method proposed in this paper, it is compared with the traditional method that selects the three sensors nearest to the target to form a coalition raised in Reference [6]. The targets are tracked for 30 s and Fig. 7 shows the comparison result of energy consumption. The blue line represents the total energy consumption per second by traditional method, while the red line is the total energy consumption per second by the method proposed.

When there are three targets and 60 randomly distributed sensors, the computing time of MEM at each sampling interval is 0.703 s which can satisfy the demand of real-time performance. According to the iteration of MEM, the receptive field

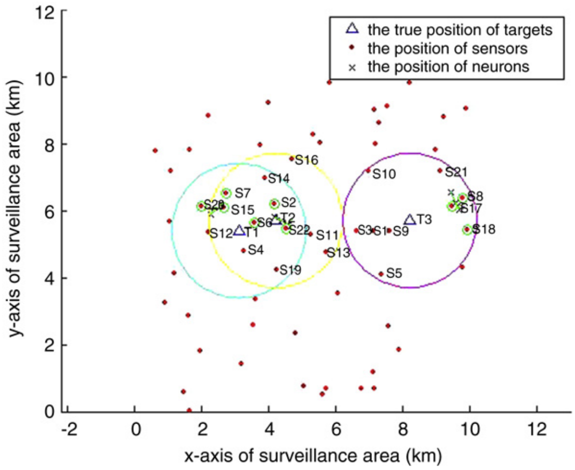

Fig. 5. The network state after iteration and the coalition members locked.

Table 1
Simulation Results of MEM at $t = 16$ s.

	Target coordinates	Sensors in the coalition	Localization result of coalition	Opti. method energy (J)	Trad. method energy (J)
$T1$	(3.25, 5.1)	$S7, S15, S20$	(3.268, 5.058)	0.093	0.850
$T2$	(4.0, 5.4)	$S2, S6, S22$	(4.008, 5.393)	0.238	2.442
$T3$	(8.1, 5.4)	$S8, S17, S18$	(8.208, 5.469)	0.164	0.146

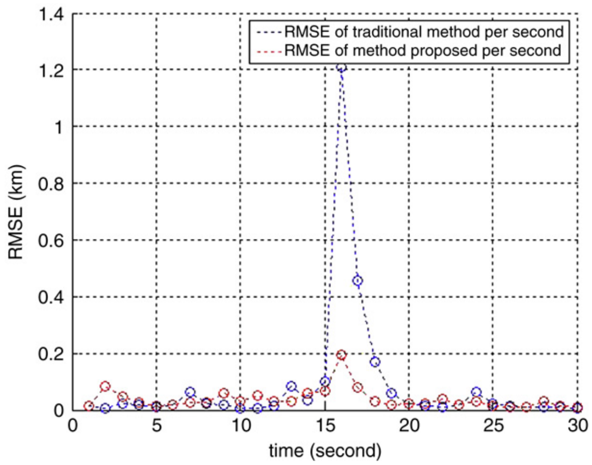

Fig. 6. The tracking error for $T3$.

representing the cost of the system is convergent all the time. After about 80 iterations, the satisfactory result of task allocation can be got. It is obvious that satisfactory cost can be got after only a few iterations.

Sensors in the blue circle can detect $T1$ and three sensors in it will be selected to form a dynamic coalition for tracking $T1$. Similarly, sensors in the yellow circle or pink circle will also be selected to form a coalition for tracking $T2$ or $T3$. At the sample interval $t = 16$ s, the trajectories of $T1$ and $T2$ become across. Without optimized task allocation algorithm, the competition and conflict for sensor resource of two coalitions is tackled by random allocation strategy and the energy consumption of the system will increase. The optimized result of task allocation based on MEM is as follows. Coalition $C1 = \{S7, S15, S20\}$, that is, sensors $S7$, $S15$ and $S15$ are designated to track target $T1$. Coalition $C2 = \{S2, S6, S22\}$, that is, sensors $S2$, $S6$ and $S22$ are designated to track target $T2$. Coalition $C3 = \{S8, S17, S18\}$, that is, sensors $S8$, $S17$ and $S18$ are designated to track target $T3$. Sensors in the area covered by both blue and yellow circles can detect $T1$ and $T2$. As a result, the competition and conflict for sensor resource of two coalitions appears. But with the task allocation algorithm, $S7$ and $S15$ join in coalition $C1$ to track $T1$, while $S2$, $S6$ and $S22$ join in coalition $C2$ to track $T2$. Table 1 shows that the energy consumption of coalition $C1$ and $C2$ will be greatly reduced by the method proposed. As Table 1 and Fig. 6 show, for target $T3$ at $t = 16$ s, if three sensors $S1$, $S3$, $S9$ nearest to the target $T3$ are selected according to traditional algorithm, the energy consumption of coalition $C3$ is 0.146 J, while using optimized algorithm three sensors $S8$, $S17$, $S18$ are selected and the energy consumption of coalition

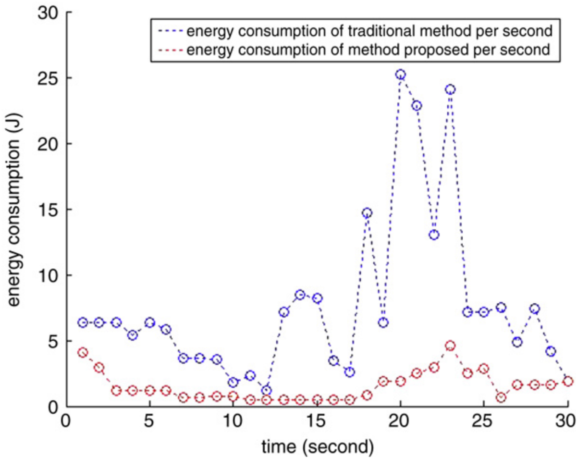

Fig. 7. The energy consumption per second of the tracking system.

$C3$ is 0.164 J. Though energy consumption for traditional algorithm is similar to the optimized algorithm or even lower, the tracking error is obviously higher than optimized algorithm. Besides, to the system comprised of three coalitions, energy consumption for optimized algorithm is much lower.

During the period of $t = 10$–25 s, just like the special time $t = 16$ s, the trajectories of $T1$ and $T2$ are across, which will brings the competition and conflict for sensor resource. As illustrated in Fig. 7, compared with traditional random allocation algorithm, it is obvious that the method proposed in this paper reduces the system energy consumption greatly.

4. Conclusions

Aiming at the task allocation of collaborative technique in wireless sensor network, a method for optimized task allocation based on elastic neural networks is proposed. Compared with conventional method, simulation results show that the energy consumption of the tracking system is reduced significantly and the tracking accuracy is improved greatly.

Collaborative target tracking is an essential capability for WSN. According to the discussion, it is clear that because of self-organizing and self-studying characteristics of this method, the performance and efficiency of the tracking system can be significantly improved and further the energy of the system can be economized that results in increasing the lifetime of the whole wireless sensor network. The main contribution of this paper is that it describes an approach that can solve the problem of resource allocation and avoid increasing energy consumption during the competition and conflict process in wireless sensor network when time and resource are constrained. The purpose of reducing energy consumption by collaborative and effective tracking multi-target among sensors is achieved.

References

[1] I.F. Akyildiz, S. Weilian, Y. Sankarasubramaniam, A survey on sensor networks, IEEE Communications Magazine 40 (8) (2002) 102–114.
[2] H. Ma, W.H. Brian, Collaborative data and information processing for target tracking in wireless sensor networks, in: Proceedings of 2006 IEEE International Conference on Industrial Informatics, 2006, pp. 647–652.
[3] L. Yang, C. Feng, J.W. Rozenblit, J. Peng, A multi-modality framework for energy efficient tracking in large scale wireless sensor networks, in: Proceedings of the 2006 IEEE International Conference on Networking, Sensing and Control, 2006, pp. 916–921.
[4] J. Chen, C. Zang, W. Liang, H. Yu, Auction-based dynamic coalition for single target tracking in wireless sensor networks, in: Proceedings of the 6th World Congress on Intelligent Control and Automation, 2006, pp. 94–98.
[5] Y. Mao, M. Liu, L. Chen, D. Chen, X. Li, A distribute energy-efficient location-independent coverage protocol in wireless sensor networks, Journal of Computer Research and Development 43 (2) (2006) 187–195.
[6] Y. Tseng, S. Kuo, H. Lee, C. Huang, Location tracking in a wireless sensor network by mobile agents and its data fusion strategies, The Computer Journal 47 (4) (2004) 448–460.
[7] L.M. Kaplan, Transmission range control during autonomous node selection for wireless sensor networks, in: Proceedings of 2004 IEEE Aerospace Conference, 2004, pp. 2072–2087.
[8] J.M. Nash, Optimal allocation of tracking resources, in: Proceedings of the IEEE Conference on Decision and Control, 1977, pp. 479–482.
[9] D.A. Castaon, Approximate dynamic programming for sensor management, in: Proceedings of the 36th IEEE Conference on Decision and Control, 1997, pp. 1202–1207.
[10] B. Xu, Z. Wang, An application of a new strategy of sensor network to the bearings-only target tracking, Journal of Astronautics 27 (3) (2006) 379–384.
[11] S. Shams, Neural network optimization for multi-target multi-sensor passive tracking, Proceedings of the IEEE 84 (10) (1996) 1442–1457.
[12] M. Liu, H. Li, N. Xu, Multi-sensor multi-target passive locating and tracking, International Journal of Control, Automation, and Systems 5 (2) (2007) 200–207.